

Uncertainty of global warming potential for milk production on a New Zealand farm and implications for decision making

Claudine Basset-Mens · Francis M. Kelliher ·
Stewart Ledgard · Neil Cox

Received: 27 April 2009 / Accepted: 25 May 2009 / Published online: 1 September 2009
© Springer-Verlag 2009

Abstract

Background, aim and scope As a food exporting nation, New Zealand recognises that the Global Warming Potential (GWP) impact of agriculture has become important to food customers. Food production policy and industry analysts make GWP decisions based on greenhouse gas inventory and life cycle assessment (LCA) results. For decision making, the level of confidence associated with information is important. However, treatment of uncertainty has been problematic in LCA, especially in agricultural systems. In this paper, the GWP of 1 kg of milk was used as a case study to test the feasibility of quantifying uncertainties by Monte Carlo simulation in an LCA applied to an agriculture product. The study also contributes to the development of good practice and has implications for the incorporation of uncertainties into decision making.

Materials and methods We distinguished between three sources of variation. First, there is variability amongst basic

units such as dairy cattle, soils and farm characteristics which may be quantified by the standard deviation (SD). Second, there is uncertainty about true population means, which is typically provided by a sample and can be measured by the standard error of the mean (SEM). Third, choices, such as the time horizon for computing GWP, can strongly affect the LCA outcomes. The first two sources were analysed by compiling input variable statistics and undertaking Monte Carlo numerical simulations. The third source of variation was quantified by sensitivity analysis.

Results Up to the farm-gate stage, the mean GWP of 1 kg of milk (computed over 100 years) was 0.96 kg CO₂-eq. The associated SD was 38% of the mean when using the SD of input variables (and called “variability”) and 7% when using the SEM (and called “uncertainty”). The GWP was most sensitive to uncertainty of pasture dry matter intake by grazing cattle. The second and third key input variables were the cattle excreta nitrous oxide emission factor and the enteric fermentation methane emission factor, respectively. Changing the GWP from a 100-year computation to one of 20 years corresponded to GWP increasing by 92%, while for a change from 100 to 500 years GWP declined by 54%. **Discussion** Data compilation for the uncertainty analyses was challenging because the measurements available were made over smaller time and space scales than ideal, so observations had to be generalised and data gaps filled by expert judgement. Uncertainty analysis using the SEM of input variables was considered most adapted in LCA, so it is recommended as best practice. Identification of the key parameters responsible for uncertainty in the LCA revealed knowledge gaps where research should be directed, such as for methane digestion and nitrous oxide emissions from N excreted by ruminants. Moreover, richer information for those key parameters could be used to build a typology of more meaningful simulations instead of a single, virtual

Responsible editor: Gérard Gaillard

C. Basset-Mens (✉)
UR HortSys, TA B-103/PS4, Boulevard de la Lironde,
34398 Montpellier Cedex 5, France
e-mail: claudine.basset-mens@cirad.fr

F. M. Kelliher
Lincoln Research Centre, AgResearch Ltd.,
Private Bag 4749,
Christchurch 8140, New Zealand

F. M. Kelliher
Agricultural & Life Sciences Division, Lincoln University,
P.O. Box 84, Lincoln 7647, New Zealand

C. Basset-Mens · S. Ledgard · N. Cox
Ruakura Research Centre, AgResearch Ltd.,
Private Bag 3123,
Hamilton, New Zealand

average for analysing environmental impacts of the agricultural system.

Conclusions The use of Monte Carlo simulations for uncertainty and sensitivity analyses of LCA estimates for an agricultural product was feasible and recommendations were made. Developing a typology of realistic simulations based on the key parameters identified in the sensitivity analysis could provide decision makers with more information. Furthermore, in comparative LCA studies, a probabilistic framework provides further information including the statistical significance of differences between technological options. This would represent considerable progress for the decision-making process.

Recommendations and perspectives We recommend that uncertainty information such as SEM, when available, be part of inventory data for agriculture systems in public reports and databases including assessment of its statistical meaning and consistency.

Keywords Decision making · Global warming potential · Life cycle assessment · Milk · New Zealand · Stochastic modelling · Uncertainty

1 Background, aim and scope

New Zealand has a unique profile of greenhouse gas (GHG) emissions amongst developed countries in being dominated by agriculture (~50%) (MfE 2004). Considerable effort has gone into refining New Zealand's agricultural emissions (de Klein et al. 2001, 2003, 2004; Sherlock et al. 2001; Clark et al. 2003; Kelliher et al. 2003, 2005) and exploring mitigation options (Clark et al. 2001; Ulyatt et al. 2002; de Klein and Ledgard 2005; de Klein et al. 2006). However, the intensification of dairy farming is increasing its relative national contribution. Decision makers seek to understand the significance of changing milk production on Global Warming Potential. The Life Cycle Assessment (LCA) methodology has proved a valuable tool for the environmental evaluation of farming systems (van der Werf and Petit 2002). It is usually used to provide a holistic picture to decision makers of the environmental problems attached to a product by studying an average or a representative system at a large scale. The results from LCA studies are affected by different sorts of variations. The first corresponds to the variation between the units we study such as dairy farms. This variability at a national scale is huge. The other sorts of variation relate to the different sources of uncertainty arising from the imperfection of the tools we use (data sets, models, choice and assumptions), to characterise and quantify average or representative LCA results for the studied system. The estimation of the uncertainty of the LCA results is then

critical to allow an assessment of its significance by political and technical stakeholders (ISO 2000; Guinée et al. 2002; Gibbons et al. 2006). Different strategies have been developed in LCA studies of agricultural products to define representative systems. The first option consists of collecting data from one "typical" farm, experimental farm or from a sample of commercial farms (Cederberg and Mattsson 2000; Haas et al. 2001; Cederberg and Darelius 2002; Casey and Holden 2005a; Thomassen et al. 2008). The statistical characteristics of the LCA results from a sample of farms can be calculated in addition to the average (Haas et al. 2001; Casey and Holden 2005a; Thomassen et al. 2008) but will only represent the variability of the studied sample. The extrapolation of these results to the national scale is therefore questionable. Given the impossibility of extrapolating these localised LCA studies of real farms to represent the national scale, the alternative is to design an average system using national statistics and databases (Carlsson-Kanyama 1998; van der Werf et al. 2005; Basset-Mens and van der Werf 2005; Casey and Holden 2005b). With this latter approach, the degree of completeness of the technical data used is good but other sources of information are required to complete the inventory and the uncertainty attached to this average result is never quantified. Amongst all the methodologies described to quantify the uncertainty of LCA results, stochastic modelling receives growing attention in LCA studies of industrial products (McCleese and LaPuma 2002; Huijbregts et al. 2003; May and Brennan 2003) but has been scarcely applied to LCA studies on agricultural products (Sandars et al. 2003; Gibbons et al. 2006). Furthermore, the uncertainty analyses presented in those papers either explore the overall variability of the LCA result (Gibbons et al. 2006) or the uncertainty of the mean (Sandars et al. 2003) which are two completely different sorts of variation. The confusion in practice between the different sorts of variation (variability, uncertainty) and the lack of harmonisation still represent an obstacle to the implementation of uncertainty analyses in LCA studies on farming systems. As a consequence, there is an urgent need for developing and harmonising uncertainty analyses in LCA studies of agricultural products and using these analyses to deliver more meaningful results for all stakeholders. Taking the Global Warming Potential of 1 kg of NZ milk as a case study, and working on an average scenario-based approach, the objectives of this paper are to:

- quantify the uncertainty of LCA results using Monte Carlo simulations according to different assumptions on the variance of input variables
- identify which assumption on the variance of input variables is most relevant to run uncertainty analyses in LCA studies

- rank the key input variables and explore the implications of these results for the decision-making process.

2 Materials and methods

2.1 Global warming potential for 1 kg of average NZ milk

The Life Cycle Assessment from “cradle-to-farm-gate” of 1 kg of average NZ milk for the season 2004–2005 has been presented in another paper (Basset-Mens et al. 2009). An average NZ dairy farm was defined based on national statistics, NZ databases and model simulations. Briefly, the farm had 315 cows, grazing 115 ha that received 114 kg of nitrogen (N) fertiliser per hectare each year. The cows consumed annually 11,300 kg DM/ha of on-farm pasture, 1,100 kg DM/ha of brought in feed supplements (maize and pasture silage produced off-farm) and produced 10,564 l of milk/hectare. The replacement animals were assumed to be grazed off-farm. The inventory of GHG emissions for 1 kg of milk was based on the IPCC-NZ methodology (de Klein et al. 2001; Clark 2001). Methane emissions were estimated by multiplying the dry matter intake of cows by the emission factor defined by Clark (2001) (see equations and variables in Section 2.2). Nitrous oxide emissions were calculated by multiplying N inputs by specific NZ emission factors corresponding to the fraction emitted to the atmosphere as N_2O (de Klein et al. 2001) (see Eq. (3)). In particular, the emission factor of nitrous oxide from grazed pasture is 1% in the NZ context compared with a default emission factor of 2% for the IPCC methodology. Concerning indirect nitrous oxide emissions, the fractions leached from excreta and fertilisers were according to Thomas et al. (2005), using the OVERSEER® nutrient budget model (Wheeler et al. 2003). The fraction volatilised from excreta and fertiliser was based on IPCC (1997). The N excreted from cows was calculated according to Ledgard et al. (2003).

2.2 Simplified equation

The contribution analysis of the main substances (not shown) was used to define a simplified equation of the GWP for 1 kg of milk. More than 57% of GWP was due to methane emissions predominantly from enteric fermentation (55%) and 33% was due to nitrous oxide emissions from soil denitrification and nitrification processes (from on-farm pasture production, off-farm pasture production, maize production). Urea manufacturing accounted for only 3.6%, agricultural operations such as tractor use (fuel consumption) for 2.4% while electricity use contributed 1.6%. Overall, the contribu-

tion from CO_2 emissions was about 10%. Methane from enteric fermentation and nitrous oxide emissions were described in detail in our simplified equation while the CO_2 component was defined only through one main variable. The latter was the CO_2 emissions from urea manufacturing (dependent on the urea rate), as calculated with the SIMAPRO software. The remaining CO_2 -equivalent emission was according to SIMAPRO calculation and was defined as a constant. This constant comprised CO_2 emissions from some secondary processes and minor methane emissions from excreta on pastures and from dairy shed effluent. This simplified equation (Eqs. (1), (2), (3) and (4)) was developed in Excel and @Risk software, with GWP (per kg of milk) defined as an output and the variables of these equations defined as risk variables.

$$GWP(/kg \text{ milk}) = E_{CO_2} \times CF_{CO_2} + E_{N_2O} \times CF_{N_2O} + E_{CH_4} \times CF_{CH_4} \quad (1)$$

where: $CF_{CO_2}=1$; $CF_{N_2O}=310$; $CF_{CH_4}=21$; E_{CO_2} , E_{N_2O} , E_{CH_4} are described in Eqs. (2), (3) and (4)

$$E_{CO_2} = [(Urea1 + Urea2 + Urea3) \times E_{CO_2(Urea)}] + 77.6 \quad (2)$$

where: $E_{CO_2(Urea)}=1,480 \text{ g } CO_2/kg \text{ urea}$;

Urea1 urea applied to on-farm pastures in kg urea per kg of milk
 Urea2 urea applied to off-farm pastures in kg of urea per kg of milk
 Urea3 urea applied to off-farm maize in kg urea per kg of milk.

$$E_{N_2O} = [(Nfert1 + Nfert2 + Nfert3) \times EF_1 + (Excreta1 + Excreta2) \times EF_3 + ((Volat_f \times (Nfert1 + Nfert2 + Nfert3) + (Volat_e \times (Excreta1 + Excreta2))) \times EF_4 + (Leach \times (Excreta1 + Excreta2 + Nfert1 + Nfert2 + Nfert3)) \times EF_5] \times 1.571 \quad (3)$$

where: $Nfert1$ =kg N fertiliser applied on on-farm pastures; $Nfert2$ =kg N fertiliser applied on off-farm pastures; $Nfert3$ =kg N fertiliser applied on off-farm maize;

Excreta1 on-farm N excreta in kg N per kg of milk (including N excreted on the dairy shed, since it is directly reapplied onto pastures);

Excreta ₂	off-farm N excreta in kg N per kg of milk;
Volat _f	fraction of N volatilised from fertiliser=0.10;
Volat _e	fraction of N volatilised from excreta=0.20;
	Leach=fraction of N leached from either excreta or fertiliser=0.07;
EF ₁	emission factor of N ₂ O as kg N–N ₂ O per kg N applied from N fertiliser=0.0125;
EF ₃	emission factor of N ₂ O as kg N–N ₂ O per kg N applied from excreta=0.01;
EF ₄	emission factor of N ₂ O as kg N–N ₂ O per kg N applied from ammonia volatilised=0.01;
EF ₅	emission factor of N ₂ O as kg N–N ₂ O per kg N applied from nitrate leached=0.025

$$E_{CH_4} = (DMI1 + DMI2 + DMI3 + DMI4) \times EF_{CH_4} \quad (4)$$

where: DMI1=on-farm pasture dry matter intake in kg per kg of milk; DMI2=off-farm pasture dry matter intake in kg per kg of milk; DMI3=on-farm hay silage dry matter intake in kg per kg of milk; DMI4=on-farm maize silage dry matter intake in kg per kg of milk;

EF_{CH₄} Emission factor of methane from dry matter intake as g CH₄ per kg DMI=21.6

2.3 Probabilistic distributions of input variables

Probabilistic distributions were defined through their coefficient of variation and their type of probabilistic function. For each risk variable, the standard error of the mean (SEM=SD/ \sqrt{n}), or simply uncertainty of the mean,

and the standard deviation (SD) were calculated or estimated and a probabilistic distribution was assumed (Tables 1 and 2). Concerning the technical data (see Table 1), the milk production was based on national statistics. The standard deviation of this variable is large due to the large variability of the overall population while the standard error of the mean is small because there were a lot of data and hence good information about the mean of the population. The on-farm dry matter intake was simulated using OVERSEER® model. The SD and the SEM for this variable were calculated using formal statistics and the SD or SEM of the input variables of that model, i.e. energy requirement of cows, energy concentration of the diet and milk production. The SD of on-farm dry matter intake was mainly dependent on the milk SD. The SEM and SD of the feed supplements and N fertiliser use were based on a large set of data: the Dexcel Profitwatch database, from surveys of NZ dairy farmers, 2000–2005. The SEM of these variables was therefore small but their SD was very large, especially for the feed supplement use, due to the variability of practices at the farm level. Finally, SD and SEM or uncertainty of the mean for off-farm variables were defined using expert estimates but represented only secondary variables. Concerning the inventory data (see Table 2), the SD of EF₁, EF₄ and EF₅ were deduced from the ranges representing 95% of the values, given by IPCC (2001). These factors have been based on a summary of data available in temperate regions and present a very large variability due to environmental factors, management-related factors and measurement-related factors (Bouwman et al. 2002). The SEM and SD for EF₃ were calculated from the NzOnet set of data (29 values), according to Kelliher et al. (2005). The

Table 1 Coefficients of variation of the mean, total coefficients of variation and probabilistic functions assumed for the key technical parameters

	Coefficient of variation of the mean (SEM) ^b	Coefficient of variation (SD) ^b	Reference for SEM and SD	Probabilistic distribution
Milk, kg/ha/year ^a	0.003	0.312	LIC statistics	Gaussian
On-farm DM pasture intake, kg/ha/year	0.07	0.34	Clark et al. (2003); Statistical calculation	Gaussian
Feed supplements (maize silage and forage), kg DM/ha/year	0.03	1.59	Dexcel database	Lognormal
Feed supplements (hay or silage), kg DM/ha/year	0.03	1.59	Dexcel database	Lognormal
On-farm pasture N fertiliser rate, kg N/ha/year	0.013	0.649	Dexcel database	Lognormal
Off-farm replacement DM pasture intake, kg/ha/year	0.10	0.20	Expert judgement	Gaussian
Off-farm replacement, N fertiliser rate, kg N/ha/year	0.10	0.20	Expert judgement	Gaussian
Off-farm feed production, N fertiliser rate, kg N/ha/year	0.10	0.20	Expert judgement	Gaussian

^a Milk's coefficient of variation is included in the calculation of the coefficient of variation of pasture DM intake

^b Expressed as a proportion of the mean

Table 2 Coefficients of variation of the mean, total coefficients of variation and probabilistic functions assumed for the inventory data

Process	Coefficient of variation of the mean (SEM) ^a	Reference for SEM	Coefficient of variation (SD) ^b	Reference for SD	Probabilistic distribution
Kg of N ₂ O–N emitted per kg of N					
Due to N fertiliser use (EF ₁)	0.21	Derived from Bouwman et al. (2002)	1.02	IPCC (2001)	Lognormal
Due to excreta deposited during grazing (EF ₃)	0.21	Kelliher et al. (2005)	1.16	Kelliher et al. (2005)	Lognormal
Due to atmospheric deposition of NH ₃ (EF ₄)	0.21	Assumed to be similar to EF ₃	0.45	IPCC (2001)	Lognormal
Due to leaching and runoff of NO ₃ (EF ₅)	0.21	Assumed to be similar to EF ₃	1.18	IPCC (2001)	Lognormal
Kg of NO ₃ –N emitted per kg of N excreted or N fertiliser applied	0.10	Ledgard and Waller (2001)	0.25	Expert judgement	Gaussian
Kg of NH ₃ –N emitted per kg of N excreted	0.14	Sherlock's data	0.41	Sherlock's data	Gaussian
Kg of NH ₃ –N emitted per kg of N fertiliser applied	0.14	Sherlock's data	0.41	Sherlock's data	Gaussian
Kg of CH ₄ emitted per tonne of DM ingested	0.04	Kelliher et al. (2007)	0.26	Clark et al. (2003)	Gaussian

^a Expressed as a proportion of the mean

SEM of EF₁ was calculated from the Bouwman et al. (2002) set of data. The SEM of EF₄ and EF₅ were assumed by default to be the same as for EF₃. The uncertainty of the mean of the fraction of N leached was deduced from Ledgard and Waller (2001) while its SD was estimated by expert judgement and corresponded to the important variability of this emission over NZ pastures (soil and climate variability). The SEM and SD of the fraction of N volatilised were based on a NZ set of data (Sherlock, unpublished). The SEM and SD of the methane emission factor were based on a NZ set of data according to Kelliher et al. (2007) and Clark et al. (2003), respectively. For most risk variables, a Gaussian distribution was assumed except for the N₂O emission factors for which a lognormal distribution was assumed as recommended by IPCC (2001) and for variables with a very large SD (feed supplements and N fertiliser rate) to avoid negative values to be selected in the simulation.

2.4 Monte Carlo simulations and sensitivity analyses

Uncertainty and sensitivity analyses were performed with @Risk package (Palisade Corporation 2002). Two Monte Carlo simulations, specifically Latin Hypercube simulations, were run:

- one using the standard error of the mean (or uncertainty of the mean) as uncertainty interval for each key parameter, and called “Uncertainty”
- one using the standard deviation, reflecting the inherent variability of the parameter across farms, and called “Variability”

Latin Hypercube simulations (LHS) were preferred because they use a technique of stratified sampling without replacement which allows for a quicker stabilisation of the results' function. Each model run consisted of 5,000 iterations (assuming independent variables). An uncertainty analysis assuming correlation factors between key variables on the basis of expert advice was also run (not shown). The final uncertainty of the GWP result was larger when assuming correlations between key variables. For the sensitivity analysis, we used the regression coefficients proposed by the @Risk software which measure for each input variable the sensitivity of the output to that particular input distribution. In this sensitivity analysis, the overall contribution of the uncertainty of each input variable to the uncertainty of the output is assessed. This therefore includes both the uncertainty of a given input variable and its sensitivity in the model.

3 Results

3.1 Frequency distributions of GWP for 1 kg of average NZ milk

For each simulation run, the mean GWP of 1 kg of milk was about 962 g CO₂-eq. The standard deviation of this result obtained with the “uncertainty” analysis was about 7% while it was 38% with the “variability” analysis. The “uncertainty” distribution was very slightly skewed (skewness of 0.23) while the “variability” distribution was significantly skewed (skewness of 1.7) (Fig. 1). The range of values

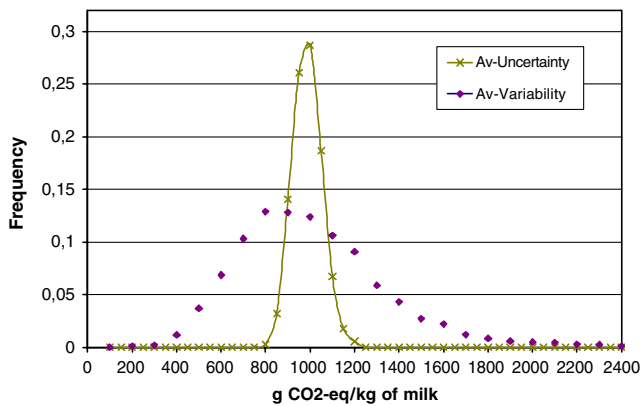


Fig. 1 Frequency distributions of GWP of 1 kg of milk for the average NZ farm according to “Uncertainty” and “Variability” analyses

obtained with the “uncertainty” analysis was 745–1197 g CO₂-eq/kg of milk. From this analysis, the upper 95% confidence limit for GWP per kg of milk was 1,073 g CO₂-eq and 90% of values were in the interval –11% to +12% around the mean. With the “variability” analysis, the range of values obtained was 125–4,672 g CO₂-eq/kg of milk and the upper 95% confidence limit for GWP per kg of milk was 1,582 g CO₂-eq. Ninety percent of values in this analysis were in the interval –48% to +64%.

3.2 Ranking of key parameters regarding their contribution to the uncertainty of results

In the sensitivity analysis from @Risk, a normalised multiple regression coefficient of 0 indicates no relationship between the input and output, while a value of 1 or –1 indicates a 1 or –1 standard deviation change in the output for a 1 standard deviation change in the input. In both analyses, the three key input variables were the same and were ranked in the same order (Table 3).

They were:

- On-farm dry matter intake
- EF₃ (emission factor for nitrous oxide due to excreta deposited during grazing)
- EF_{CH4} (emission factor for methane emitted by cows during digestion)

This was consistent with previous uncertainty analyses conducted for the separate inventory of nitrous oxide and methane emissions in NZ (Sherlock et al. 2001; Clark et al. 2003; Kelliher et al. 2007). Since the regression coefficients include both the uncertainty of the input variables and their sensitivity in the model, this ranking is also explained by the role of these parameters in the GWP model. In our model, the on-farm DM intake was the largest part of the DM intake

Table 3 Regression coefficients and ranking orders of the most influential input variables for the “Uncertainty” and the “Variability” analyses

Parameters	Regression coefficients with “Uncertainty” analysis	Ranking order	Regression coefficients with “Variability” analysis	Ranking order
On-farm DM intake	0.697	1	0.608	1
EF ₃	0.547	2	0.553	2
EF _{CH4}	0.323	3	0.376	3
Off-farm DM intake	0.203	4	0.077	9
EF ₁	0.200	5	0.187	5
EF ₄	0.126	6	0.047	10
EF ₅	0.123	7	0.132	6

of cows and was included in the calculation of the two key components of our model output: the methane and the nitrous oxide components (as commented in Section 2.2 regarding the contribution analysis of the GWP). This is why this input variable was identified as the first variable contributing to the uncertainty of the output and the emission factors used to calculate the nitrous oxide (EF₃) and methane emissions (EF_{CH4}) were logically the next key parameters to which both the result and its uncertainty were sensitive.

4 Discussion

4.1 Use of Monte Carlo simulations to quantify uncertainty of LCA results for farming systems and contribution to harmonised practice

The objective of this paper was firstly to test and examine Monte Carlo simulations to quantify the uncertainty of LCA results of agricultural products, using the GWP of 1 kg of NZ milk as a case study. In one analysis, the standard deviation of each key input variable was used while in the other, the uncertainty of the mean was used (standard error of the mean calculated or estimated) to characterise the probabilistic distributions of each input variable. As already highlighted by several authors (Payraudeau et al. 2007; Björklund 2002; Heijungs and Huijbregts 2004), the lack of information on the uncertainty of data is an important difficulty for the development of uncertainty analyses in general. This problem is even more critical for Monte Carlo simulations where one needs to define a probabilistic distribution for all input variables (Payraudeau et al. 2007). The lack of statistics for inventory

data (SD, SEM, confidence interval or total range) results in an additional and time-consuming phase for estimating their probabilistic functions according to a range of means: using a set of data, literature references or by default, expert judgement. Furthermore, this discrepancy in the quality of the information on the uncertainty of input variables (e.g. on-farm and off-farm DM intakes in our analysis) can result in inconsistencies in the analysis. However, the systematic practice of presenting confidence intervals for data is increasing (IPCC 2001; Dones et al. 2005; Frischknecht et al. 2005) and should be encouraged (Payraudeau et al. 2007). Although challenging, the two different uncertainty analyses using Monte Carlo simulation were feasible. However, their meaning is different. The “variability” analysis corresponds to variability among units including dairy cattle, farms, soils and climate. The “uncertainty” analysis, on the contrary, is an estimate of the imprecision of our average result due to the different and cumulated uncertainties in our input estimates. It tells how confident we are in this average result. The “variability” cannot be reduced since it refers to the real variability of GWP of dairy farms at the NZ scale. The “uncertainty” can potentially be reduced through the improvement of our data and precision of tools. From a decision-maker perspective, the existence of the natural variability is known but when attached to a result it does not help them make a decision. Generally speaking, in LCA studies, decision makers need to base their judgement on representative scenarios at various scales for which the results are known with a sufficiently good level of confidence. The “uncertainty” analysis as presented in this study appears more logical for LCA studies and interesting for decision makers. However, the “variability” analysis potentially reveals some potential for improvements of the GWP of dairy farms. Analysing the conditions in terms of practice and natural conditions leading to the lowest GWP per kg of milk could also be helpful to make decisions such as the identification of the most favourable regions where producing milk.

These analyses only accounted for the uncertainty/variability of parameters and data. Uncertainty due to choice of the time horizon was taken into account through a sensitivity analysis using the set of characterisation factors calculated by Houghton et al. (1996) for the time horizons of 20 and 500 years in addition to the reference horizon of 100 years. Comparing this range of results with the “uncertainty” interval or even the “variability” interval due to inventory data (see Section 3.1) (indicated by the 5% and 95% percentiles from the @Risk software calculations), the choice of time horizon resulted in the largest variation, from –54% to +92% around the average result (not shown), against –11% to +12% for the “uncertainty” and –48% to +64% for the “variability”.

4.2 Deliver more meaningful results to stakeholders

Another purpose of this study was to analyse the implications of these results for the decision-making process. Both “uncertainty” and “variability” analyses allowed us to produce an LCA result for the GWP impact as a probabilistic distribution. In addition to the mean, a range of probable results can be presented with a certain degree of confidence. As a rule, we consider this presentation of LCA results is extremely valuable for decision makers who need to know the robustness of the assessment of alternative systems such as new technologies and the risk attached to their decisions. We also consider, as part of more transparent LCA studies, that the choice of the degree of confidence can be left to decision makers. The ranges of results for different degrees of confidence could be presented to them to support their decision and to help them determine an acceptable level of risk (which might often be less than 95%). Moreover, using the “uncertainty” analysis as recommended in this study would often lead in practice to a clear ranking between two technological options, the uncertainty interval reinforcing the meaning of the results. Conversely, when using the “variability” analysis, the interval would be large and would add confusion to the decision-making process.

In view of producing more meaningful results, the key parameters identified in the sensitivity analysis were used to differentiate the average scenario. The methane emission factor was not used in this differentiation process since the current estimate already corresponds to the best knowledge available in NZ and the set of data could not be differentiated further. Realistic scenarios were designed and assessed by differentiating different soil drainage

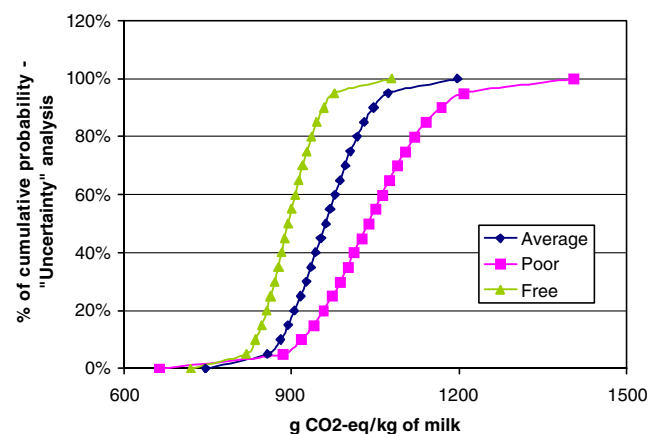


Fig. 2 Cumulative probability distributions of GWP (using “Uncertainty” analysis) for average, poorly drained soil and free drained soil scenarios of dairy farm

classes (poorly drained versus free draining soil situations), a real parameter influencing both remaining key variables: on-farm DM intake and EF_3 in our case study. The measurement data collected in the NzOnet study (de Klein et al. 2004) were used for differentiating EF_3 . Pasture yield was adjusted for each soil situation based on expert judgement. The cumulative probability curves of the GWP, using the “uncertainty” analysis, are presented in Fig. 2 for the two differentiated and the average scenarios. According to this analysis, the probability that the GWP for the free drained scenario is different from the GWP for the poorly drained scenario was around 70%. Although we can consider these results (see Fig. 2) and their corresponding mean and attached uncertainty more meaningful than a sole average result, the differentiation process was also shown to be limited by existing data.

As presented in this paper, LCA results are affected by different sources of variation which require specific methods to be evaluated. Uncertainty due to data can be addressed through Monte Carlo simulations while uncertainty due to choices requires the effect on results of each choice to be tested in a sensitivity analysis. Although these different uncertainty analyses cannot be aggregated into a single uncertainty interval, they give different perspectives to decision makers. Furthermore, choices such as time horizon for computing characterisation factors can be seen as arbitrary and therefore the uncertainty analysis due to data can either be repeated for each arbitrary choice of time horizon or their choice can be made arbitrarily and transparently for one given analysis. In studies where the CO_2 emissions contribution to GWP is high, the effect of the time horizon would be less compared to studies where the methane and nitrous oxide components are paramount. This is explained by the conversion of methane or nitrous oxide into carbon dioxide after the end of their life time in the atmosphere which, over a long period of time, diminishes their GWPi.

5 Conclusions and recommendations

Taking the GWP of 1 kg of average NZ milk as a case study, stochastic modelling has been applied and discussed in this paper. This approach could similarly be implemented to other important impact categories within an LCA study such as eutrophication, energy use and acidification. There would however be a need for accounting in the model for the interactions between these different impact categories. The difficulties of defining probabilistic distributions for input variables of LCA studies have been highlighted, reflecting imperfections in such analyses. Nevertheless, the diagnoses were valuable and there is increasing availability of informa-

tion on the uncertainty of data and of user-friendly analysis tools (e.g. @Risk; SIMAPRO). Our study showed that applying stochastic modelling to LCA studies of agricultural products was possible and could probably be developed in a routine way for LCA studies in the near future. It is however critical to make sure that uncertainty intervals presented in the databases have clear and defined meanings. This study suggested the standard error of the mean (or uncertainty of the mean) was most adapted and informative for LCA studies and can contribute to reconcile decision makers with uncertainty. When data are available, a differentiation process could be explored to deliver more meaningful results. Both the uncertainty analysis and the differentiation process are strongly dependent on the existence of good sets of data for key variables at the national scale. Regarding the GWP of 1 kg of NZ milk, and despite the existence in NZ of one of the most comprehensive sets of data on methane digestion and nitrous oxide emissions from N excreted by ruminants, our findings support the need for further research in these two areas to reduce uncertainty.

Acknowledgement Funding for this research came from the New Zealand Foundation for Research, Science and Technology.

References

- Basset-Mens C, van der Werf HMG (2005) Scenario-based environmental assessment of farming systems: the case of pig production in France. *Agric Ecosyst Environ* 105:127–144
- Basset-Mens C, Ledgard S, Boyes M (2009) Eco-efficiency of intensification scenarios for milk production in New Zealand. *J Ecol Econ* 68:1615–1625
- Björklund A (2002) Survey of approaches to improve reliability in LCA. *Int J LCA* 7(2):64–72
- Bouwman AF, Boumans LJM, Batjes NH (2002) Modeling global annual N_2O and NO emissions from fertilized fields. *Glob Biogeochem Cycles* 16(4):1080. doi:10.1029/2001GB001812
- Carlsson-Kanyama A (1998) Energy consumption and emissions of greenhouse gases in the life-cycle of potatoes, pork meat, rice and yellow peas. Technical report 26 ISSN1104-8298. Department of Systems Ecology, Stockholm, Sweden
- Casey JW, Holden NM (2005a) The relationship between greenhouse gas emissions and the intensity of milk production in Ireland. *J Environ Qual* 34(2):429–436
- Casey JW, Holden NM (2005b) Analysis of greenhouse gas emissions from the average Irish milk production system. *Agric Syst* 86:97–114
- Cederberg C, Darelus K (2002) Using LCA methodology to assess the potential environmental impact of intensive meat production. In: Cederberg C (ed) *Life Cycle Assessment of animal production*, Thesis, Department of Applied Environmental Science. Göteborg University, Göteborg, Sweden
- Cederberg C, Mattsson B (2000) Life cycle assessment of milk production—a comparison of conventional and organic farming. *J Clean Prod* 8:49–60

- Clark H (2001) Ruminant methane emissions: a review of the methodology used for national inventory estimations. Report for Ministry of Agriculture and Fisheries, Wellington, New Zealand
- Clark H, de Klein C, Newton P (2001) Potential management practices and technologies to reduce nitrous oxide, methane and carbon dioxide emissions from New Zealand agriculture. Report prepared for Ministry of Agriculture & Forestry
- Clark H, Brookes I, Walcroft A (2003) Enteric methane emissions from New Zealand ruminants 1990 and 2002 calculated using an IPCC Tier 2 approach
- De Klein CAM, Ledgard SF (2005) Nitrous oxide emissions from New Zealand agriculture—key sources and mitigation strategies. *Nutr Cycl Agroecosyst* 72:77–85
- De Klein CAM, Sherlock RR, Cameron KC, van der Weerden TJ (2001) Nitrous oxide emissions from agricultural soils in New Zealand—a review of current knowledge and directions for future research. *J R Soc N Z* 31(3):543–574
- De Klein CAM, Barton B, Sherlock RR, Li Z, Littlejohn RP (2003) Estimating a nitrous oxide emission factor for animal urine from some New Zealand pastoral soils. *Aust J Soil Res* 42:381–399
- De Klein CAM, Li Z, Sherlock RR (2004) Determination of the N₂O emission factors from animal excreta or urea fertiliser, following a winter application in two regions of New Zealand. A final report of an NzOnet study from August 2003 to June 2004. Client report, prepared for Ministry of Agriculture & Forestry
- De Klein CAM, Smith LC, Monaghan RM (2006) Restricted autumn grazing to reduce nitrous oxide emissions from dairy pastures in Southland, New Zealand. *Agric Ecosyst Environ* 112:192–199
- Dones R, Heck T, Faist Emmenegger M, Jungbluth N (2005) Life cycle inventories for the nuclear and natural gas energy systems, and examples of uncertainty analysis. *Int J LCA* 10(1):10–23
- Frischknecht R, Jungbluth N, Althaus H-J, Doka G, Dones R, Heck T, Hellweg S, Hirschler R, Nemecek T, Rebitzer G, Spielmann M (2005) The Ecoinvent Database: overview and methodological framework. *Int J LCA* 10(1):3–9
- Gibbons JM, Ramsden SJ, Blake A (2006) Modelling uncertainty in greenhouse gas emissions from UK agriculture at the farm level. *Agric Ecosyst Environ* 112:347–355
- Guinée JB, Gorée M, Heijungs R, Huppes G, Kleijn R, de Koning A, van Oers L, Wegener Sleeswijk A, Suh S, Udo de Haes HA, de Bruijn H, van Duin R, Huijbregts MAJ (2002) Life cycle assessment. An operational guide to the ISO standards. Centre of Environmental Science, Leiden University, Leiden
- Haas G, Wetterich F, Köpke U (2001) Comparing intensive, extensified and organic grassland farming in southern Germany by process life cycle assessment. *Agric Ecosyst Environ* 83:43–53
- Heijungs R, Huijbregts MAJ (2004) A review of approaches to treat uncertainty in LCA. In: Pahl C, Schmidt S, Jakeman T (eds) *iEMSs 2004 International Congress: "Complexity and Integrated Resources Management"*. International Environmental Modelling and Software Society, Osnabrueck June 2004
- Houghton JT, Meira Filho LG, Callander BA, Harris N, Kattenberg A, Maskell K (1996) *Climate change 1995: the science of climate change*. Cambridge University Press, Cambridge
- Huijbregts MAJ, Gilijsse W, Ragas ADMJ, Reijnders L (2003) Evaluating uncertainty in environmental life-cycle assessment. A case study comparing two insulation options for a Dutch one-family dwelling. *Environ Sci Technol* 37:2600–2608
- IPCC (1997) Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories: Reference Manual (3). Chapter 4: Agriculture. Intergovernmental Panel on Climate Change. Paris, France. Available at: <http://www.ipcc-nggip.iges.or.jp/public/gl/invs6.htm>
- IPCC (2001) Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories, Chapter 4: Agriculture. Intergovernmental Panel on Climate Change. Paris, France, 94 p
- ISO (2000) ISO 14043: environmental management—Life cycle assessment—Life cycle interpretation. Geneva, Switzerland
- Kelliher FM, Ledgard SF, Clark H, Walcroft AS, Buchan M, Sherlock RR (2003) Revised nitrous oxide emissions from New Zealand agricultural soils: 1990–2001. Final client report, prepared for the Ministry of Agriculture & Forestry
- Kelliher FM, Dymond JR, Arnold GC (2005) Kyoto compliance analysis of uncertainties in New Zealand's methane and nitrous oxide emissions inventories with respect to 1990 levels. Final client report prepared for Ministry for the Environment
- Kelliher FM, Dymond JR, Arnold GC, Clark H, Rys G (2007) Estimating the uncertainty of methane emissions from New Zealand's ruminant animals. *Agric For Meteorol* 143:146–150
- Ledgard SF, Waller JE (2001) Precision of estimates of nitrate leaching in OVERSEER®. Client report prepared for FertResearch
- Ledgard S, Luo J, Monaghan R (2003) Partitioning of excreta nitrogen from grazing animals into urine and dung nitrogen. Report for MAF. Wellington, New Zealand, 14 p
- May JR, Brennan DJ (2003) Application of data quality assessment methods to an LCA of electricity generation. *Int J LCA* 8(4):215–225
- McCleese DL, LaPuma PT (2002) Using Monte Carlo simulation in life cycle assessment for electric and internal combustion vehicles. *Int J LCA* 7(4):230–236
- MfE (2004) New Zealand's Greenhouse Gas Inventory 1990–2002. The National Inventory Report and Common Reporting Format Tables. Ministry for the Environment, Wellington, New Zealand
- Palisade Corporation (2002) Guide to using @RISK. Risk analysis and Simulation Add-In for Microsoft® Excel—Version 4.5, New York, United States of America
- Payraudeau S, van der Werf HMG, Vertès F (2007) Analysis of the uncertainty associated with the estimation of nitrogen losses from farming systems. *Agric Syst* 94(2):416–430
- Sanders DL, Audsley E, Cañete C, Cumby TR, Scotford IM, Williams AG (2003) Environmental benefits of livestock manure management practices and technology by life cycle assessment. *Biosyst Eng* 84(3):267–281
- Sherlock R, Johnston G, Kelliher F, Newsome P, Walcroft A, de Klein C, Ledgard S (2001) A desktop study of regional variations in nitrous oxide emissions. Client report, prepared for the Ministry of Agriculture and Forestry
- Thomas SM, Ledgard SF, Francis GS (2005) Improving estimates of nitrate leaching for quantifying New Zealand's indirect nitrous oxide emissions. *Nutr Cycl Agroecosyst* 73:213–226
- Thomassen MA, Van Calster KJ, Smits MCJ, Iepema GL, de Boer IJM (2008) Life cycle assessment of milk production systems in the Netherlands. *Agric Syst* 96:95–107
- Ulyatt MJ, Clark H, Lassey KR (2002) Methane and climate change. *Proc N Z Grassl Assoc* 64:153–157
- Van der Werf HMG, Petit J (2002) Evaluation of the environmental impact of agriculture at the farm level: a comparison of twelve indicator-based methods. *Agric Ecosyst Environ* 93(1):131–145
- Van der Werf HMG, Petit J, Sanders J (2005) The environmental impacts of the production of concentrated feed: the case of pig feed in Bretagne. *Agric Syst* 83(2):153–177
- Wheeler DM, Ledgard SF, De Klein CAM, Monaghan RM, Carey PL, McDowell RW, Johns KL (2003) OVERSEER® nutrients budgets—moving towards on-farm resource accounting. *Proc N Z Grassl Assoc* 65:191–194